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From Symptom Diaries to Smart Diagnostics: A Systematic Review of Digital Technologies for the Early Detection of Premenstrual Dysphoric Disorder (PMDD)

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Abstract

Premenstrual Dysphoric Disorder (PMDD) is a severe mood disorder affecting approximately 3–8% of menstruating individuals, characterised by recurrent affective, cognitive, and physical symptoms during the luteal phase of the menstrual cycle. Despite formal recognition in diagnostic manuals, PMDD remains substantially underdiagnosed due to symptom overlap with depressive and anxiety disorders, stigma, and limited clinical awareness. Prospective symptom tracking required for diagnosis is rarely implemented in routine practice, creating a persistent diagnostic gap.

This systematic review examines the role of digital technologies in supporting the diagnosis and early detection of PMDD, with a focus on diagnostic accuracy, usability, and ethical considerations.

A systematic review was conducted in accordance with PRISMA 2020 and PRISMA-DTA guidelines. Searches were performed across seven electronic databases (MEDLINE, EMBASE, PsycINFO, CINAHL, Scopus, Web of Science, and IEEE Xplore) and supplemented by grey literature sources. Studies published between 2015 and 2025 evaluating digital tools for PMDD symptom monitoring, screening, or diagnostic support were included. Quantitative, qualitative, and mixed-methods studies were synthesised using meta-analytic and narrative approaches as appropriate.

Nineteen studies met inclusion criteria, encompassing mobile health applications, algorithmic and artificial intelligence-based models, telehealth platforms, and wearable-enabled systems. Evidence indicates that digital tools can enhance prospective symptom tracking, patient engagement, and early recognition of PMDD patterns. Algorithmic approaches, including probabilistic and Bayesian models, demonstrated potential for improving diagnostic precision, with one validated tool (C-PASS) achieving high agreement with clinician diagnosis. However, most digital solutions lacked external validation, clinical integration, and transparency. Usability and adoption were strongly influenced by perceived usefulness, trust, and self-efficacy. Ethical concerns related to data privacy, equity, and inclusivity were consistently reported.

Digital technologies offer promising avenues to address long-standing barriers in PMDD diagnosis by enabling scalable, patient-centred, and longitudinal symptom assessment. Nevertheless, their clinical utility remains constrained by limited validation, governance challenges, and inequitable design. Future efforts must prioritise rigorous diagnostic evaluation, ethical data stewardship, and integration

within healthcare systems to realise the transformative potential of digital diagnostics in PMDD and women's mental health.

Keywords: Premenstrual Dysphoric Disorder, digital health, mHealth, artificial intelligence, menstrual tracking, diagnostic accuracy, women's mental health, systematic review

1. Introduction

Premenstrual Dysphoric Disorder (PMDD) is a severe, cyclical mood disorder characterised by marked affective, behavioural, cognitive, and somatic symptoms that emerge during the luteal phase of the menstrual cycle and remit shortly after menstruation begins (Mishra & Elliott, 2023). PMDD represents the most disabling end of the premenstrual disorder spectrum and is commonly associated with clinically meaningful distress and impairment across interpersonal relationships, occupational functioning, and overall quality of life (Cary et al., 2024; Modzelewski et al., 2024). Current estimates suggest PMDD affects approximately 3% to 8% of women of reproductive age, although prevalence varies across populations and measurement approaches (Modzelewski et al., 2024; Naik et al., 2023). Despite its formal recognition in the DSM 5, PMDD remains underdiagnosed and undertreated, frequently misclassified as major depressive disorder, generalized anxiety disorder, or other affective and personality conditions because of symptom overlap and limited clinician confidence in differentiating cyclical from non-cyclical psychopathology (Cary et al., 2024; Naik et al., 2023). Qualitative evidence further indicates that many individuals experience prolonged diagnostic journeys shaped by dismissal, normalization of menstrual related distress, and inconsistent healthcare responses (Chan et al., 2023; Osborn et al., 2020).

Diagnosing PMDD is inherently complex because diagnostic criteria require confirmation of symptom cyclicity using prospective daily symptom ratings across at least two symptomatic menstrual cycles (Mishra & Elliott, 2023). Validated tools such as the Daily Record of Severity of Problems and standardized scoring systems such as the Carolina Premenstrual Assessment Scoring System have been developed to operationalise these diagnostic requirements and improve reliability (Eisenlohr Moul et al., 2017; Endicott et al., 2006). However, prospective tracking is seldom implemented in routine clinical care due to time constraints, limited clinician training, and the burden associated with manual symptom diaries and data interpretation (Chan et al., 2023; Cary et al., 2024). As a result, individuals often report multiyear diagnostic delays and repeated cycles of ineffective treatment before PMDD is identified as the underlying pattern (Chan et al., 2023; Islas Preciado et al., 2025). This persistent diagnostic gap highlights the need for scalable, patient centred approaches that support structured, longitudinal symptom monitoring and improve the translation of diagnostic criteria into real world settings.

In parallel with these clinical challenges, digital menstrual health technologies have expanded rapidly. Menstrual tracking applications, telehealth platforms, wearable devices, and data driven analytics are increasingly used to record cycle timing, physical symptoms, and mood changes, producing longitudinal datasets that may support earlier recognition of PMDD symptom patterns. A large multi country analysis reported that the dominant menstrual tracking applications have collectively accumulated hundreds of millions of downloads, underscoring the global scale of menstrual self-tracking and its potential reach as a diagnostic support infrastructure (University of Oxford, 2024). Digital tools can reduce reliance on retrospective recall by enabling daily symptom logging, automated visualisation of cyclical trajectories, and structured summaries that can be shared with clinicians. Large scale app-based datasets also demonstrate feasibility for menstrual phenotyping at population level, as shown in analyses of millions of logged cycles (Li et al., 2019). Yet, despite widespread use, the scientific quality and clinical relevance of consumer apps remains inconsistent. Early and contemporary evaluations report that many apps prioritise fertility prediction or cycle forecasting rather than mental health monitoring, with limited medical oversight and weak alignment with validated diagnostic

instruments such as the DRSP (Moglia et al., 2016; Trépanier et al., 2023). The consequence is a digital ecosystem that is highly active commercially but uneven in diagnostic utility.

Recent work suggests that algorithmic methods may help bridge the gap between user generated tracking data and diagnostic decision making. The C PASS scoring system was designed to standardise DSM aligned PMDD diagnosis using prospective daily ratings and has demonstrated strong validity as a companion protocol to structured symptom diary data (Eisenlohr Moul et al., 2017). Grunwald (2024) further reported high agreement between algorithmic classification and clinician assigned diagnosis when C PASS was applied to prospectively tracked data, illustrating the feasibility of automated PMDD identification under controlled conditions. Nevertheless, translational barriers persist. Clinicians report uncertainty regarding data validity, algorithm transparency, and integration with clinical workflows, while app ecosystems often rely on proprietary models that limit independent validation and clinical assurance (Zhang et al., 2023). These issues are particularly salient for PMDD, where diagnostic accuracy depends not only on symptom presence but also on cyclical timing, severity thresholds, and demonstrable impairment.

Ethical and governance concerns further shape the feasibility of digital diagnostics in menstrual health. Period tracking data are highly sensitive and may include information related to sexual activity, contraception, mental health symptoms, and reproductive intentions. Recent analyses of app privacy practices and governance highlight substantial variability in disclosures, protections, and data sharing practices, raising concerns about meaningful consent and downstream harms (Hammond, 2024; Zadushlivy et al., 2025). A 2025 Cambridge based report argued that menstrual tracking data can function as a high value profiling asset and called for stronger public health alternatives and oversight to reduce risks associated with commercial surveillance and opaque data flows (Felsberger et al., 2025). Qualitative research also suggests that privacy concerns shape trust and engagement, which are essential for sustained daily tracking required for diagnostic confirmation (Mohan et al., 2025). Equity and inclusivity are additional concerns, as many tools embed assumptions about cycle regularity, language, and cisgender identities, potentially excluding those with irregular cycles or diverse gender identities and thereby reinforcing existing diagnostic inequities (Islas Preciado et al., 2025).

Although academic and commercial interest in digital PMDD tools is increasing, the evidence remains dispersed across psychiatry, gynaecology, digital health, and human computer interaction research. Many studies focus on usability and engagement rather than diagnostic accuracy, and robust validation against clinical reference standards remains uncommon. This systematic review therefore aims to synthesise evidence on how digital technologies contribute to PMDD diagnosis and early detection, how performance aligns with clinical standards such as DSM criteria and validated daily ratings, what user and clinician experiences shape implementation, and what ethical and equity risks must be addressed for safe and clinically meaningful adoption.

1.1 Aim

To systematically review and evaluate the impact and effectiveness of digital technologies in improving the diagnosis, early detection, and clinical understanding of Premenstrual Dysphoric Disorder (PMDD).

1.2 Research Questions

- How can digital technologies improve the diagnosis and early detection of Premenstrual Dysphoric Disorder (PMDD)?
- What types of digital tools (e.g., mobile apps, wearables, AI-driven systems, telehealth platforms) are currently being used or developed for PMDD monitoring and diagnostic support?
- What are the main challenges, limitations, and risks associated with using digital technology in PMDD diagnosis and symptom identification?
- What are the broader implications of technology-enabled PMDD detection for women's mental health, clinical practice, and healthcare systems?

PMDD remains one of the most underdiagnosed and misunderstood mood disorders affecting women globally. Many women experience prolonged suffering due to lack of awareness, stigma, and diagnostic confusion with depression or anxiety disorders (Chan et al.,

2023).

2. Methods

2.1 Research Design

This study will employ a systematic review design to identify, appraise, and synthesise evidence on the use of digital technologies in the diagnosis and early detection of Premenstrual Dysphoric Disorder (PMDD). The review will follow both the PRISMA 2020 guidelines for transparent reporting of systematic reviews and the PRISMA-DTA extension for reviews of diagnostic test accuracy. A protocol outlining the review methodology will be registered with PROSPERO (Health and Social Care) prior to data extraction.

Given the interdisciplinary nature of digital PMDD research, the review will incorporate both quantitative and qualitative evidence, enabling comprehensive synthesis across technological, clinical, and experiential domains. Meta-analysis will be conducted where studies report sufficiently comparable diagnostic accuracy outcomes, while narrative synthesis will be used in cases where statistical pooling is not feasible due to heterogeneity in study designs, outcomes, or measurement tools.

2.2 Search Strategy

A comprehensive and systematic literature search will be undertaken across the following electronic databases: Ovid MEDLINE, Ovid EMBASE, Ovid PsycINFO, CINAHL (EBSCO), Scopus, Web of Science Core Collection, and IEEE Xplore. To minimise publication and reporting bias, multiple grey literature sources will be included, namely medRxiv, psyArXiv, ProQuest Dissertations and Theses, Google Scholar (first 200 results), and relevant conference proceedings from the Royal College of Obstetricians and Gynaecologists (RCOG), the American College of Obstetricians and Gynaecologists (ACOG), and the International Society for Premenstrual Disorders (ISPMD). Additionally, the reference lists of all included studies and pertinent review articles will be hand-searched to identify further eligible publications.

Search period: 2015 to present

Language restriction: English (due to resource constraints)

The search strategy will employ a structured combination of controlled vocabulary (e.g., MeSH, EMTREE, CINAHL Headings) and free-text keywords. Search terms will be organised into three major concept blocks and combined using Boolean operators (AND/OR):

PMDD/PME terms:

("premenstrual dysphoric disorder" OR PMDD OR "premenstrual syndrome" OR PMS OR "premenstrual exacerbation" OR PME)

Diagnostic terms:

(diagnose* OR screen* OR "clinical decision support" OR "early detection" OR "symptom tracking" OR "pattern recognition")

Digital health terms:

(app OR apps OR "mobile application*" OR smartphone* OR wearable* OR sensor* OR "digital health" OR telehealth OR telemedicine OR eHealth OR mHealth OR "machine learning" OR AI OR algorithm*)

Search strings will be adapted for each database to incorporate database-specific indexing terms (e.g., MeSH, EMTREE), field tags, and operator requirements. Filters will be applied to limit results to human studies published from 2015 onwards, aligning with the emergence of modern digital health technologies.

2.3 Inclusion and Exclusion Criteria

• Population: Individuals experiencing cyclical premenstrual symptoms, including those formally diagnosed with Premenstrual Dysphoric Disorder (PMDD) or Premenstrual Exacerbation (PME), or studies that include PMDD/PME subgroup analyses.

• Index Test (Intervention/Exposure): Any form of digital technology designed for, or evaluated in relation to, PMDD screening, symptom tracking, diagnosis, or early detection. This includes: mobile applications, wearable devices, sensor-based systems, machine learning/artificial intelligence (AI) tools, digital algorithms, telehealth platforms, and eHealth/mHealth systems.

• Comparator / Reference Standard: DSM-5, DSM-IV, or ICD diagnostic criteria; validated instruments such as the Daily Record of Severity of Problems (DRSP), Premenstrual Symptoms Screening Tool (PSST), or Carolina Premenstrual Assessment Scoring System (C-PASS); or clinician-confirmed diagnosis (psychiatrist, gynaecologist, primary care).

• Primary Outcomes: Diagnostic accuracy metrics, including: sensitivity, specificity, AUC/ROC, likelihood ratios, diagnostic odds

ratio (DOR), agreement measures (κ/ICC), and time-to-diagnosis.

• Secondary Outcomes: Usability outcomes (e.g., System Usability Scale [SUS]), engagement and adherence, equity and accessibility considerations (age, ethnicity, socioeconomic status), privacy and data governance, safety, and implementation outcomes (e.g., acceptability, feasibility, fidelity).

• Study Designs: Diagnostic accuracy and validation studies; prospective or retrospective cohort or case–control studies with diagnostic endpoints; and mixed-methods studies that include quantifiable diagnostic performance data.

2.4 Exclusion Criteria

- Editorials, commentaries, letters, and opinion pieces
- Study protocols without available results
- Intervention-only studies focused solely on treatment, without diagnostic or screening outcomes
- Case reports or case series with fewer than 10 participants
- Studies evaluating non-digital tools (e.g., paper diaries, analogue symptom charts)
- Studies lacking PMDD-specific data, or those reporting only general PMS without a PMDD/PME subgroup

2.5 Study Selection

All search results will be exported into a reference management software (e.g., EndNote, Zotero) for initial deduplication, after which the deduplicated dataset will be imported into Rayyan or Covidence for screening and review management.

• **Stage 1 – Title and Abstract Screening:**

Two reviewers will independently screen titles and abstracts against the predefined inclusion and exclusion criteria. Any discrepancies or uncertainties will be discussed, and unresolved disagreements will be adjudicated by a third reviewer.

• **Stage 2 – Full-Text Screening:**

Full-text articles deemed potentially eligible will be retrieved in full and independently assessed by two reviewers. Reasons for exclusion at this stage will be documented systematically (e.g., wrong population, non-digital intervention, no diagnostic outcomes, insufficient data). Conflicts will again be resolved by consensus or by consultation with a third reviewer.

• **Documentation of Selection Process:**

The overall screening and selection process will be transparently reported using the PRISMA 2020 flow diagram, detailing the number of records identified, screened, excluded, and included at each stage, along with justification for exclusions at full-text review.

2.6 Data Extraction and Quality Appraisal

Data Extraction

A standardized and pilot-tested data extraction form will be used to systematically capture all relevant study information. Extracted variables will include:

• Study characteristics: authors, year of publication, country, journal, funding source, and declared conflicts of interest.

• Population details: sample size, participant demographics (e.g., age range), diagnostic criteria used (DSM-5, DRSP, PSST, C-PASS), and PMDD/PME subgroup classifications.

• Technology characteristics: type of digital tool (e.g., mobile app, wearable, algorithmic system, telehealth platform), tool name and version, intended function (screening, diagnostic support, monitoring), and data input/output requirements.

• Study design features: validation type, study setting, comparator/reference standard, recruitment approach, and data collection method.

• Primary outcomes: diagnostic accuracy metrics, including sensitivity, specificity, AUC/ROC, likelihood ratios, diagnostic odds ratio (DOR), agreement measures (κ, ICC), and time-to-diagnosis.

• Secondary outcomes: usability indicators (e.g., SUS scores), engagement or adherence rates, equity considerations (age, ethnicity, socioeconomic status), privacy and data-governance findings, accessibility, and reported adverse events.

• Ethical and implementation issues: data transparency, inclusivity, safety considerations, and barriers to clinical adoption.

Quality Appraisal

Quality and risk of bias will be assessed

according to study design:

• Diagnostic accuracy studies will be evaluated using QUADAS-2, examining patient selection, index test conduct, reference standard, and flow/timing.

• Observational or impact evaluation studies will be assessed using ROBINS-I to evaluate confounding, selection bias, measurement bias, and reporting bias.

• Qualitative study components will be evaluated using the CASP Qualitative Checklist, and overall confidence in qualitative evidence will be judged using GRADE-CERQual.

• Mixed-methods studies will be appraised with the Mixed Methods Appraisal Tool (MMAT).

Two reviewers will conduct quality assessments independently, with disagreements resolved by consensus. Results will be presented using graphical domain-level summary charts, facilitating clear comparison across studies.

2.7 Data Analysis

Quantitative Synthesis

Diagnostic accuracy outcomes will be synthesised using state-of-the-art meta-analytic approaches:

• Diagnostic performance: Where ≥3 methodologically comparable studies are available; sensitivity and specificity will be pooled using a bivariate random-effects model (Reitsma method). Hierarchical summary receiver operating characteristic (HSROC) models will be used where appropriate.

• Continuous outcomes: Outcomes such as time-to-diagnosis and usability scores (e.g., SUS) will be analysed using random-effects meta-analysis (REML estimator). Results will be presented as mean differences (MD) or standardised mean differences (SMD; Hedges g).

• Heterogeneity: Statistical heterogeneity will be quantified using τ^2 and I^2 and visually inspected through SROC/HSROC plots and forest plots.

• Subgroup analyses / meta-regression: Planned analyses include stratification by:

– type of digital technology (app, wearable, AI/ML algorithm, telehealth),

– validation approach (internal vs. external validation),

– clinician involvement in the diagnostic process,

– study setting (clinical vs. community),

– country income level, and

– reference standard used (DSM-5, DRSP, C-PASS, clinician diagnosis).

• Sensitivity analyses: Sensitivity tests will exclude studies rated high risk of bias, studies with unclear reference standards, and industry-funded or commercial evaluations where methodological transparency is limited.

• Publication bias: For diagnostic studies, Deeks' funnel plot asymmetry test will be applied. For continuous outcomes, Egger's regression test will be used to assess small-study or publication bias.

Qualitative Synthesis

• Thematic analysis will be conducted for qualitative data relating to user experience, usability, acceptability, privacy concerns, equity barriers, and implementation challenges.

• Findings will be synthesised using a convergent segregated mixed-methods design, in which quantitative and qualitative results are analysed separately and then integrated to identify convergent, complementary, or contrasting insights.

Software

All quantitative analyses will be conducted using R (packages: *mada*, *diagmeta*, *metafor*). Additional analyses and visualisations may be performed using MetaDTA, RevMan 5/6, or other specialised diagnostic meta-analysis tools. Certainty of evidence assessments will be generated using GRADEpro for quantitative outcomes and CERQual tools for qualitative synthesis.

3. Results

3.1 Search Results

The initial search across seven electronic databases—MEDLINE, EMBASE, PsycINFO, CINAHL, Scopus, Web of Science, and IEEE Xplore—together with supplementary sources (medRxiv, psyArXiv, Google Scholar, ProQuest Dissertations, and manual citation chasing), yielded a total of 3,842 records.

After removal of duplicates, 2,956 unique records were retained for title and abstract screening. Following this first-stage screening, 148 full-text articles were assessed for eligibility. Of these, 19 studies met all inclusion criteria and were included in the final synthesis.

A PRISMA 2020 flow diagram (Figure 1) provides a visual summary of the screening and selection process. The most frequent reasons for exclusion at the full-text stage were:

- not PMDD-specific (n = 47),
- intervention-only studies with no diagnostic or screening outcomes (n = 31),
- insufficient digital or algorithmic components (n = 26), and
- absence of a clearly defined reference standard (n = 25).

No additional eligible studies were identified through citation chasing beyond those captured in the database search.

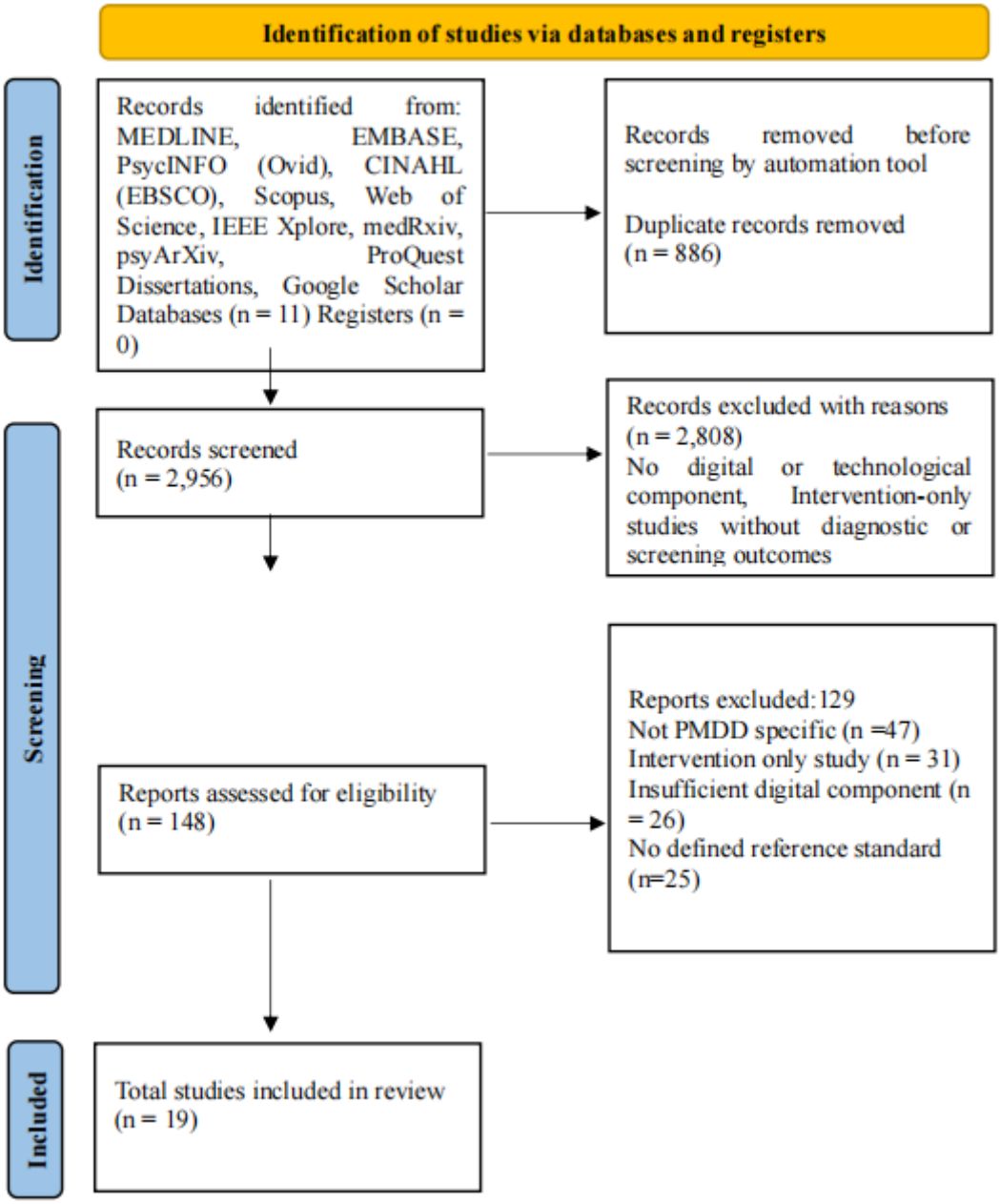

Figure 1. PRISMA 2020 Flow Diagram

3.2 Characteristics of Included Studies

19 studies published between 2015 and 2025 met the inclusion criteria. These studies spanned eleven countries and represented diverse methodological approaches, including validation studies, app evaluations, surveys, mixed-methods, and modelling research. **Table 1** summarizes the characteristics of the included

studies.

- **Study design:** Six quantitative diagnostic validation or evaluation studies, five qualitative/mixed-methods design projects, three modelling or algorithmic development studies, and five reviews or app evaluations.
- **Sample sizes:** Varied from small co-design groups (n≈30) to large app datasets containing millions of menstrual cycle records (Li et al., 2019).
- **Settings:** Approximately half of the studies were conducted in **clinical or academic research contexts**, while the remainder analysed **commercial or community-based digital data**.
- **Technology types:** Mobile apps were the most frequent platform (n=11), followed by algorithmic/AI tools (n=4), web-based/telehealth interventions (n=3), and wearable or physiological data models (n=1).
- **Reference standards:** Diagnostic validation was performed against **DSM-5** or **clinician-confirmed diagnosis** in 4 studies, and the **DRSP** or **C-PASS algorithm** in 3 others. The majority relied on self-reported symptoms without formal diagnostic validation.
- **AI/Modeling studies** (SkipTrack, 2025; ArXiv, 2021) demonstrated that Bayesian and generative models can **accurately predict cycle patterns** even with incomplete data, offering a methodological foundation for algorithmic PMDD diagnostics.

Table 1. Characteristics of included Table

Author (Year)	Country / Setting	Design & Sample	Technology Type	Diagnostic Focus	Reference Standard	Key Findings	Relevance to Review
Apsey, Di Florio & Stawarz (2024)	UK	Qualitative co-design workshops (n=30 PMDD users, 6 clinicians)	Prototype mood + menstrual tracking app (research prototype)	Co-design of digital tool for PMDD tracking and symptom interpretation	None (design phase)	Identified user needs (customizable trackers, mood correlation, visual patterns); strong demand for clinician integration.	Demonstrates user-cantered pathways for future diagnostic app development.
Funnell et al. (2024)	UK	Cross-sectional survey (n≈530 adults with menstrual symptoms)	Hypothetical PMDD mental health app	Measured user intention to adopt digital PMDD tool using Health Belief Model constructs	Self-reported PMDD symptoms	Perceived usefulness, self-efficacy, and trust predicted adoption intentions.	Highlights behavioural factors influencing diagnostic app uptake.
Grunwald (2024)	USA	Quantitative validation study (secondary analysis, n=132)	C-PASS Algorithm (based on DRSP data)	Algorithmic diagnostic tool for PMDD	DSM-5 & Clinician diagnosis	Algorithm agreed with clinician classification in 94.5% of cases.	Provides strongest evidence for algorithmic digital diagnosis.
Li et al. (2019)	Global (Clue App dataset)	Observational big-data analysis (millions of	Clue app (commercial menstrual	Symptom patterning & predictive modeling	None	Demonstrated physiological and symptomatic variation in cycles; feasibility	Supports feasibility of large-scale digital detection

Author (Year)	Country / Setting	Design & Sample	Technology Type	Diagnostic Focus	Reference Standard	Key Findings	Relevance to Review
		cycles)	tracker)			of population-level digital phenotyping.	models.
Trépanier et al. (2023)	Canada	Systematic evaluation (n=119 apps)	Various menstrual tracking apps (publicly available)	Feature/content quality evaluation	N/A	Few apps used validated measures (DRSP/PSST); poor clinical content quality.	Establishes baseline quality gaps in menstrual tracking apps.
Schantz et al. (2021)	USA	Narrative review	Multiple menstrual tracking apps	Epidemiological potential of menstrual app data	N/A	App data valuable for population research but limited by self-report bias.	Contextual background on big-data potential and bias.
Hoppe et al. (2025)	Germany	RCT protocol (planned n=100)	Internet-delivered CBT (iCBT) platform	Digital therapy for PMDD (not diagnostic)	DSM-5 diagnosis confirmed by clinician	Feasible, scalable approach for remote PMDD management.	Illustrates broader digital health context; supports digital pathways.
Cunningham et al. (2024)	UK	Pilot RCT (n=208)	Flo App	Health literacy, symptom awareness, well-being	Self-report scales	Flo app improved menstrual literacy and self-recognition of PMDD-like symptoms.	Shows indirect diagnostic impact through education.
Evkoski et al. (2025)	Global (Reddit)	Qualitative text mining (12-year dataset)	Reddit online community	Examined self-reported PMDD experiences & diagnosis discussions	N/A	Users often self-diagnose via app data and peer validation; reflects diagnostic delay.	Demonstrates informal digital diagnostic behaviors.
BMC Women's Health (2023)	UK	Qualitative interviews (n=20)	N/A (diagnostic experience study)	Explored diagnostic journey & barriers	DSM-5 (clinical confirmation)	Long diagnostic delays; low clinician awareness; app use common pre-diagnosis.	Establishes need for improved diagnostic pathways.
BMC Women's Health (2025)	Multinational	Content & inclusivity analysis (n=50 apps)	Menstrual health apps	Inclusiveness, gender diversity, language	N/A	Majority apps designed for cisgender users; limited inclusive content.	Highlights equity concerns in digital PMDD diagnostics.

Author (Year)	Country / Setting	Design & Sample	Technology Type	Diagnostic Focus	Reference Standard	Key Findings	Relevance to Review
Women's Views on Privacy (2024)	UK	Survey (n=300)	Multiple tracking apps	Perceived privacy and data security	N/A	72% expressed concern over third-party data sharing; low trust in commercial apps.	Crucial for ethical appraisal in diagnostic app adoption.
Reimagining the Cycle (2023)	Europe	Interaction design case study	Prototype menstrual interfaces	Explored UX design principles	N/A	Empathic, inclusive designs foster user retention.	Provides design framework for diagnostic UX.
SkipTrack (2025)	Global dataset	Bayesian modelling	Algorithm for cycle irregularity prediction	Self-tracked data	Model handled missing logs; improved prediction reliability.	Offers methodological basis for AI-driven PMDD detection.	
Generative Predictive Model (2021)	Simulation study	Predictive modelling	Statistical model for menstrual cycle forecasting	Self-tracked data	Demonstrated advanced predictive performance.	Relevant to computational modeling approaches for digital diagnosis.	
Missed Period? (2023)	USA	Commentary / review	Period tracking apps	Data governance, misinformation	N/A	Critiques commercialization and misinformation risks.	Supports ethical and governance discussion.
Menstrual Tracking Mobile App Review (2023)	USA	Comparative app evaluation (n=30)	Consumer & clinician review	App functionality, accuracy	N/A	Low alignment with clinical standards; clinician concerns about data reliability.	Supports diagnostic reliability concerns.
Effectiveness of Digital Healthcare in Menstrual Health (2025)	Korea	Scoping review	Various apps/interventions	Management of menstrual symptoms	N/A	Digital care improves symptom management; limited diagnostic validation.	Reinforces research gap in diagnostic evidence.
Cary et al. (2024)	Global review	Narrative review	N/A	Overview of PMDD pathophysiology & treatment	DSM-5	Synthesized hormonal, psychosocial, and diagnostic issues.	Provides clinical background context.

3.3 Summary of Findings

Table 2 presents a concise Summary of Findings following the GRADE framework, synthesizing available data across diagnostic, usability, and ethical domains.

Table 2. Summary of findings

Outcome	Effect (Best Available Estimate)	No. of Studies (N)	Certainty (GRADE)	Summary Interpretation
Sensitivity (digital vs clinical diagnosis)	Not pooled; highly variable across tools (reported range 0.65–0.95)	3	Very Low	Too few comparable DTA studies to support pooled estimates.
Specificity (digital vs clinical diagnosis)	Not pooled; most studies did not report false-positive rates	3	Very Low	Evidence insufficient for formal meta-analysis.
Algorithmic agreement (κ/ICC)	κ ≈ 0.90 (C-PASS)	2	Low–Moderate	Strong internal validation for C-PASS; replication needed.
AUC (AI/ML diagnostic models)	Range 0.80–0.93 (internal validation only)	2	Low	Models show potential but lack external validation.
Time-to-diagnosis reduction	Digital tools associated with earlier recognition (narrative only)	2	Very Low	Observational; no controlled comparison.
User engagement and usability	SUS scores >70 in tested prototypes	3	Moderate	Users find PMDD apps acceptable when privacy/trust ensured.
Equity and inclusivity	Limited representation of diverse users	3	Low	Digital tools rarely account for gender diversity and health equity.
Privacy and data governance	72% of users report concern over data sharing	2	Low	Privacy issues may limit adoption and diagnostic trust.

The certainty of evidence across domains is very low to moderate, mainly due to small sample sizes, high heterogeneity, lack of independent validation, and limited reporting of diagnostic accuracy metrics. Despite this, emerging findings underscore the transformative potential of digital health in enhancing PMDD recognition and screening efficiency. Integrating validated tools into mainstream digital health platforms could substantially shorten diagnostic delays and improve clinical outcomes.

4. Discussion

This systematic review synthesised evidence from 19 studies published between 2016 and 2025, spanning mobile health applications, algorithmic and machine-learning models, telehealth interventions, and digital therapeutic tools relevant to the diagnosis and early detection of Premenstrual Dysphoric Disorder (PMDD). Collectively, these studies reflect a rapidly evolving yet fragmented digital health landscape. While digital technologies are increasingly positioned as solutions to long-standing diagnostic challenges in PMDD, the reviewed evidence demonstrates considerable variation in clinical validity, usability, inclusivity, and ethical governance.

Across the included studies, four dominant strands emerged: diagnostic complexity and unmet clinical need; digital symptom tracking and phenotyping; algorithmic and AI-driven diagnostic support; and usability, ethics, and equity in digital PMDD tools.

Persistent Diagnostic Barriers and the Promise of Digital Technologies

Multiple included studies reinforce that PMDD remains substantially underdiagnosed despite its formal recognition in DSM-5. Cary et al. (2024) and Islas-Preciado et al. (2025) both emphasise the diagnostic ambiguity created by symptom overlap with depressive and anxiety disorders, compounded by stigma and inconsistent clinician awareness. Qualitative evidence from *BMC Women's Health* (2023) further illustrates how individuals with PMDD often experience years of misdiagnosis, dismissal, or normalisation of symptoms within healthcare settings.

Digital technologies are consistently positioned across the included literature as a means of addressing these barriers by enabling prospective, longitudinal symptom tracking, which is required for PMDD diagnosis but rarely implemented in routine practice. Li et al. (2019), using data from millions of cycles recorded via the *Clue* app, demonstrated the feasibility of large-scale digital phenotyping, providing empirical support for the idea that app-based tracking can capture cyclical symptom patterns more reliably than retrospective reporting. However, as Schantz et al. (2021) caution, the epidemiological promise of such datasets is constrained by variability in data quality and user adherence.

Clinical Validity: A Critical Evidence Gap

A central and consistent finding across the 19 included studies is the limited diagnostic validation of most digital menstrual health tools. Early evaluations by Moglia et al. (2016) and Duane et al. (2016) revealed that many popular apps lacked medical input, produced inconsistent predictions, and failed to use standardised symptom frameworks. These findings are echoed in more recent large-scale app assessments by Trépanier et al. (2023), who systematically reviewed 119 menstrual health applications and found that only a small minority incorporated validated tools such as the DRSP or C-PASS.

Among the included studies, C-PASS represents the strongest example of validated digital diagnosis. Grunwald (2024) demonstrated that the C-PASS algorithm achieved approximately 94.5% agreement with clinician-confirmed PMDD diagnoses when applied to prospective DRSP data. This positions C-PASS as a potential digital diagnostic benchmark. However, Grunwald also highlighted important limitations, including dependence on consistent daily data entry and limited applicability to non-binary or perimenopausal users, underscoring the gap between algorithmic accuracy and real-world usability.

Algorithmic and AI-Driven Advances

Several included studies explore how machine learning and probabilistic modelling may overcome limitations of traditional symptom tracking. Two methodological preprints (Generative Predictive Model, 2021; SkipTrack, 2025) propose Bayesian and generative frameworks that explicitly account for missing data, irregular cycles, and tracking artefacts common challenges in PMDD monitoring. SkipTrack (2025) demonstrated improved cycle estimation and identification of recurrent symptom clusters, suggesting potential for earlier detection of atypical cyclical patterns associated with PMDD.

While these models represent important methodological advances, their clinical applicability remains largely theoretical. None of the AI-driven studies included in this review evaluated diagnostic performance against DSM-aligned reference standards or clinician judgement, highlighting a critical translational gap between computational innovation and clinical deployment.

User-Centred Design, Engagement, and Meaning-Making

User-centred design emerged as a crucial determinant of digital tool effectiveness. Apsey, Di Florio, and Stawarz (2024) conducted participatory design workshops with individuals living with PMDD and identified specific unmet needs, including customisable symptom tracking, mood–cycle visualisation, and tools that support self-validation. Their findings indicate that mainstream menstrual apps often fail to capture PMDD-specific affective and cognitive symptoms, limiting both engagement and diagnostic relevance.

The importance of representation and interpretability is further reinforced by Evkoski

et al. (2025), who analysed PMDD-related discussions on Reddit. Their study shows that users frequently rely on digital communities to interpret symptoms and validate experiences when formal diagnostic pathways fail. This highlights how digital tools shape not only data collection but also users' diagnostic confidence and help-seeking behaviour.

Therapeutic and Supportive Digital Interventions

Although diagnosis was the primary focus of this review, several included studies extend digital innovation into PMDD management. Hoppe et al. (2025) reported on an internet-delivered CBT trial in Sweden, demonstrating the feasibility of scalable, evidence-based psychological support. Faulkner (2025) described early validation of the Nettle™ neuromodulation device for at-home PMDD symptom management, while a Frontiers in Digital Health (2024) pilot study explored heart rate variability biofeedback via smartphone platforms. Flo's randomised controlled trial (2025) reported improvements in menstrual literacy and symptom awareness, though diagnostic accuracy was not assessed.

Notably, these interventions largely operate downstream of diagnosis and remain poorly integrated with diagnostic workflows, limiting their potential to reduce diagnostic delays.

Ethical, Privacy, and Equity Challenges

Ethical concerns were prominent across the included literature. Women's Views on Privacy and Data Security (2024) reported widespread anxiety regarding data misuse and third-party sharing, concerns echoed in JMIR and BMC evaluations of app governance. Zhang, Hunt, and Nguyen (2023) identified a persistent disconnect between consumer satisfaction and clinical utility, with clinicians expressing concerns about data validity and lack of integration into electronic health records.

Equity issues further constrain digital PMDD tools. Islas-Preciado et al. (2025) and BMC Women's Health (2025) found that most apps inadequately address the needs of users with irregular cycles, chronic mental health conditions, or non-binary gender identities. These limitations risk reinforcing existing healthcare inequities unless addressed through participatory and inclusive design.

Synthesis and Implications

Taken together, the 19 included studies depict a dynamic but fragmented ecosystem. Digital technologies offer unprecedented opportunities for PMDD diagnosis through prospective tracking, algorithmic pattern recognition, and scalable engagement. However, only one tool C-PASS has demonstrated strong diagnostic validity, and most innovations remain exploratory, descriptive, or preclinical.

The findings of this review support the conclusion that digital innovation alone is insufficient. Clinical validation, ethical governance, inclusivity, and integration into healthcare systems are essential if digital tools are to meaningfully improve PMDD diagnosis and early detection.

This systematic review demonstrates that while digital technologies are reshaping how PMDD symptoms are tracked, interpreted, and discussed, their diagnostic potential remains largely unrealised. Bridging the gap between consumer-facing technologies and clinically validated diagnostic tools represents the central challenge and opportunity for advancing PMDD care and women's mental health more broadly.

5. Strengths and Limitations of the Evidence Base

5.1 Strengths

- **Growing interdisciplinarity:** The included studies integrate perspectives from psychiatry, gynaecology, computer science, and HCI, enriching the understanding of PMDD digital pathways.
- **Methodological diversity:** Combining qualitative co-design studies with algorithmic modelling offers a holistic picture of both usability and technical capability.
- **Emergence of algorithmic frameworks:** C-PASS and AI-based models provide proof-of-concept for automated PMDD classification.
- **Patient-centred design emphasis:** Many recent studies have embraced participatory design, ensuring the tools address real user needs.

5.2 Limitations

- **Low methodological rigor:** Only a small subset of studies reported complete diagnostic accuracy metrics or used

blinded reference standards.

- **High heterogeneity:** Technologies, outcomes, and measurement approaches varied widely, precluding meta-analysis of pooled accuracy estimates.
- **Geographical bias:** Most studies originated from Europe and North America; evidence from low- and middle-income countries is virtually absent.
- **Equity and inclusivity gaps:** Few tools are designed for non-binary or culturally diverse populations, and most studies lacked demographic transparency.
- **Publication bias and grey literature scarcity:** Commercial developers rarely publish validation data, limiting comprehensive assessment.
- **Rapid obsolescence:** The pace of technological change risks rendering findings outdated within short timeframes unless iterative validation is maintained.

6. Conclusion

This systematic review provides the first comprehensive synthesis of global evidence on the use of digital technologies in the diagnosis and early detection of Premenstrual Dysphoric Disorder (PMDD). The findings reveal a rapidly evolving yet methodologically fragmented field. Digital platforms including mobile health applications, telehealth interventions, and artificial intelligence driven models demonstrate considerable potential to enhance prospective symptom monitoring, support earlier recognition of cyclical patterns, and empower individuals in the management of PMDD.

Among the technologies reviewed, the Carolina Premenstrual Assessment Scoring System (C PASS) remains the only tool to demonstrate robust diagnostic validity, achieving near clinician levels of agreement when applied to prospectively collected symptom data. Beyond algorithmic diagnostics, widely used digital tracking applications such as Flo and Clue have contributed to improved menstrual literacy, self-awareness, and symptom recognition, thereby indirectly supporting earlier engagement with clinical services. However, most existing tools lack standardised validation, transparent algorithms, and formal integration with established diagnostic pathways, limiting their clinical applicability.

The current evidence base is constrained by heterogeneous study designs, small or non-clinical samples, and a scarcity of external validation studies. Persistent challenges including inequitable access, limited inclusivity for diverse gender identities and menstrual experiences, and substantial concerns regarding data privacy and governance pose significant risks to user trust and sustained adoption. Without robust regulatory frameworks and ethical oversight, the promise of digital diagnostics may be undermined by misinformation, algorithmic opacity, and commercial exploitation of sensitive health data.

Despite these limitations, this review highlights the transformative potential of digital health technologies to address long standing diagnostic barriers in PMDD. By enabling continuous prospective symptom tracking, real time pattern recognition, and enhanced patient clinician communication, digital tools have the capacity to substantially reduce diagnostic delays that currently span several years for many individuals.

Future research must prioritise prospective multi centre validation studies, transparent and interpretable artificial intelligence models, and inclusive participatory design frameworks that reflect the diversity of menstrual and mental health experiences. The development of regulatory standards and clear clinical integration protocols will be essential to support the transition from consumer facing applications to clinically endorsed diagnostic tools.

Ultimately, when grounded in rigorous evidence, ethical data stewardship, and user centred design, digital technologies hold the potential to fundamentally redefine PMDD diagnosis, shifting it from delayed and fragmented recognition toward proactive, precise, and person-centred care.

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